Integrated Sensing and Processing (ISP) Phase II: Demonstration and Evaluation for Distributed Sensor Networks and Missile Seeker Systems

Progress Report:

2nd Quarter 2005 Progress Report
1 June 2005 - 31 August 2005

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Progress Report

CDRL A001 No. 02
Second Quarterly Progress Report for Period of Performance
1 June 2005 – 31 August 2005

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EXECUTIVE SUMMARY

The primary goal of this effort is to bring to maturity a select set of basic algorithms, hardware, and approaches developed under the Integrated Sensing and Processing (ISP) Phase I program, implement them on representative hardware, and demonstrate their performance in a realistic field environment. We have identified a few promising research thrusts investigated in ISP Phase I where field demonstrations are cost prohibitive but collected data sets are available. Here, we will conduct a thorough performance evaluation.

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0. Technical Abstract

Advances in sensor technologies, computation devices, and algorithms have created enormous opportunities for significant performance improvements on the modern battlefield. Unfortunately, as information requirements grow, conventional network processing techniques require ever-increasing bandwidth between sensors and processors, as well as potentially exponentially complex methods for extracting information from the data. To raise the quality of data and classification results, minimize computation, power consumption, and cost, future systems will require that the sensing and computation be jointly engineered. ISP is a philosophy/methodology that eliminates the traditional separation between physical and algorithmic design. By leveraging our experience with numerous sensing modalities, processing techniques, and data reduction networks, we will develop ISP into an extensible and widely applicable paradigm. The improvements we intend to demonstrate here are applicable in a general sense; however, this program will focus on distributed sensor networks and missile seeker systems.

1.0. Management Overview and Summary

1. A. Program Summary

The Raytheon Company, Missile Systems (Raytheon) ISP Phase II program is a twenty-four month contract with a Period of Performance (PoP) covering 1 March 2005 to 28 February 2007. Raytheon has four universities and one small business as ISP Phase II subcontractors: Arizona State University (ASU); Fast Mathematical Algorithms and Hardware (FMAH); Georgia Institute of Technology (Georgia Tech); Melbourne University (UniMelb) and the University of Michigan (UM).

1. B. Program Status

The Program status can be summarized as “on track.” All of the subcontractors are now under subcontract. UM has a Letter of Subcontract allowing them to accrue charges while final subcontract negotiations are completed. Raytheon is currently running below its spending plan to better align with the subcontractor schedules; however, we expect to complete the contract on time and budget. As of 15 August 2005, 12% of contract funds had been expended with 21% of the program complete. The contract also reflects substantial under-runs due to delays in receiving the initial invoices from the university subcontractors. We should recover from the spending profile deviation and expect to finish the contract on time and budget.

1. C. Personnel Associated/Supported

Raytheon

Dr. Harry A. Schmitt	Principal Investigator
Mr. Donald E. Waagen	Co-Principal Investigator
Dr. Sal Bellofiore	Distributed Sensing Lead
Dr. Robert Cramer	Mathematical Support
Mr. Craig Savage	Waveform Design and Control Lead
Dr. Nitesh Shah	High Dimensional Processing Data Lead

ASU

Professor Darryl Morrell
Professor Antonia Papandreou-Suppappola

FMAH

Professor Paolo Barbano
Professor Ronald Coifman

<u>Georgia Tech</u>

Professor David Anderson
Professor Paul Hasler

<u>UniMelb</u>

Dr. Barbara LaScala
Professor William Moran
Dr. Darko Musicki
Dr. Sofia Suvorova

<u>UM</u>

Professor Al Hero

<u>Significant Personnel Actions:</u> There was one significant personnel change during the current PoP. Mr. Craig Savage was transferred to Raytheon International Support Company (RISCO) to accommodate his long term assignment to Australia. Mr. Donald Waagen was promoted to Engineering Fellow and Dr. Nitesh Shah was promoted to Principal Engineer.

1. D. Recent Accomplishments and Events

We have received the Algorithms Verification Units (AVU), comprised of the Crossbow wireless low-power sensor nodes and their associated sensors, needed for distributed processing demonstrations and evaluations. Laboratory space has been identified at Raytheon in Building M09. Export Control Numbers have been obtained for the AVUs and a subset of these will be shipped to UniMelb by 15 August 2005. The remaining AVUs are available for distribution to other university personnel when needed.

A Technical Interchange Meeting (TIM) for the Georgia Tech Cooperative Analog Digital Signal Processor (CADSP) imager was held at the Office of Naval Research (ONR) on 2 June 2005. The TIM covered the status, risks and possible demonstrations/evaluations for the Georgia Tech CADSP imager. Dan Purdy (ONR) ran the TIM, which was attended by Carey Schwartz (DARPA), Harry Schmitt (Raytheon), Don Waagen (Raytheon), Nitesh Shah (Raytheon), Paul Hasler (Georgia Tech), David Anderson (Georgia Tech) and Al Hero (UM). A follow-up CADSP TIM was held at Georgia Tech on August 4 that focused on refining test and demonstration plans. David Anderson and Paul Hasler hosted the TIM; attendees from outside of Georgia Tech included Don Waagen and Nitesh Shah from Raytheon, Darryl Morrell and Antonia Papandreou-Suppappola from ASU and Al Hero from UM. Together with the ONR CADSP TIM, these meetings completed the CDRL requirement for a CADSP TIM.

1. E. Near Term Events

An amended Technical Assistance Agreement (TAA) was submitted to the U.S. State Department. The amended TAA was received by the U.S. State Department in June 2005 and is currently under review. The amended TAA expands the technical scope to cover the research areas added under the ISP Phase II program as well as covering two additional UniMelb personnel, Darko Musicki and Sofia Suvorova, who are dual citizens of Serbia and Montenegro, and Russia, respectively.

Harry Schmitt and Sal Bellofiore will spend 27 August 2005 to 4 September 2005 working with UniMelb personnel on the development and implementation of sensor scheduling and distributed tracking algorithms on the AVUs. Sal Bellofiore present an overview of the mechanics of working with the AVUs. Sal will then install the AVU control and support software on the UniMelb computers and will work with and assist UniMelb personnel to program the AVUs.

A draft technical report on waveform design and scheduling was submitted to Raytheon by FMAH. A first set of comments was returned to FMAH on 20 July 2005. This report is a contract deliverable and is due by 1 October 2005.

2.0. Technical Progress and Accomplishments

During the current PoP, we have focused on six technical areas.

1. Mathematical formulation for the implementation and demonstration of Optical Flow algorithms on Georgia Tech CADSP imager.
2. Analyses for potential Georgia Tech CADSP imager algorithms that could be implemented on the uncooled infrared imaging sensor (UCIR) on the NetFires Non-Line of Sight (NLOS) Precision Attack Munition (PAM) development program.
3. Mathematical Analyses for Distributed Sensing Demonstrations. One focus area is the development of accurate and scaleable sensor self-localization approaches. Other technical areas of particular emphasis are the development of distributed tracking and sensor scheduling algorithms.
4. The evaluation of High Dimensional Data Processing algorithms on dual polarization radar field data.
5. Stochastic approaches for Unmanned Aerial Vehicle (UAV) control and passive geolocation.
6. Waveform library selection using a policy-finding algorithm via T-step reinforcement learning.

The next several subsections describe the technical approaches for Raytheon and for each subcontractor in greater detail.

2. A. Technical Progress

2.A.1. Raytheon Technical Progress

2.A.1.a. Distributed Sensor Demonstration

Wireless low-power sensor networks have gained much deserved attention in many research fields. With the advent of low-cost digital signal processors, wireless sensor networks have begun to emerge in many applications. Some of these applications are in the field of environmental monitoring including air quality, micro-climates and soil moisture monitoring. Many structural engineering firms have also adopted wireless networks to examine vibrations in bridges and buildings, especially in earthquake prone zones. Even biologists have employed wireless networks in their field to track endangered animal more efficiently. In the military, wireless networks are utilized to monitor military perimeters and national borders. In many of these applications self-localization is essential to determine the nodes' relative distance to one another, and further, if a node within the network is equipped with a Global Positioning System (GPS) sensor board, the network can be more precisely localized. One compelling application being pursued by Raytheon under the DARPA Information Exploitation Office (IXO) Networked Embedded System Technology (NEST) program is shooter localization through acoustic ranging. To locate the shooter more accurately, several wireless nodes are deployed within an area; thus, these nodes are self-localized first before the localizing the shooter. NEST has identified accurate and scalable localization algorithms as a critical program need.

In fact, self-localization is a key component of a wide variety of distributed wireless sensing applications, including perimeter monitor and the detection and tracking of targets. Because such sensor networks will be laid down in an *ad hoc* configuration consisting of thousands of sensor nodes, accurate and scalable localization algorithms are critical to many, if not most, defense or homeland security applications.

The current generation of shooter localization algorithm is an acoustic ranging algorithm by Vanderbilt University (VU). The concept of this algorithm is based on measuring the time of arrival (TOA) of the sound signal between the signal source (actuator) and the acoustic sensor. The acoustic ranging algorithm has demonstrated localization accuracy sufficient for a proof-of-principle, and VU is developing an approach that should significantly improve localization accuracy. This new approach uses radio frequency instead of acoustic frequency for the ranging algorithm [Maroti2005]. Thus, this new approach provides more accurate localization with larger networks since radio waves propagate further than acoustic waves. However, both the baseline and improve VU self-localization algorithms rely on a genetic algorithm-based optimization approach which scales very poorly with the number of sensor nodes. As an alternative to the VU self-localization approach, we consider an algorithm based on concepts we are exploring for processing of high dimensional data. This algorithm uses the Multi-Dimensional Spectral (MDS) method.

The classical MDS algorithm was designed to construct a set of coordinates, in n dimensions, which preserve a set of pair-wise distance measurements provided in a dissimilarity matrix. If all distances between all pairs of coordinates are known (even though the coordinates themselves be unknown), the algorithm accurately computes a solution, which is unique up to a rotation and a translation. However, in the scenario of distributed, wireless sensor networks, it is not generally possible to measure all pair-wise distances, and we must be satisfied to work only with a subset of distance measurements, for example between nearest neighbors. The ISOMAP algorithm was designed for this case, and proceeds by estimating the missing measurements by constructing a multi-hop path between two unconnected nodes by summation of short hops from each pair of connected nodes along the way. In this manner the unknown distances are approximated, and upon constructing a full matrix of pair-wise distances the classical MDS is applied to obtain the final solution.

To compare the MDS algorithm with the baseline VU algorithm, we have collected data from three different test runs. The ranging data or the relative distances among the nodes are collected using the VU self-localization algorithm. Subsequently, the positions of the nodes in a Cartesian grid are determined first by using the VU algorithm (genetic-based algorithm), and then by using the MDS algorithm.

The current version of the VU algorithm that we have has a problem in the flood-routing routine (a routine that polls the environment to determine the available nodes for collecting TOA data) which causes packet collision, and ultimately, nodes not being scheduled. Figure 1 shows the position of the nodes from one of our best test run with a mean error of 10.6 cm and a standard deviation of 8.8 cm between the actual position and the measured position of the nodes. On the other hand, Figure 2 shows our worst run where the mean error is 111 cm and the standard deviation is 54.8 cm. Also, note that both figures display a number of nodes not reporting any data which are the nodes that never got scheduled due to the flood-routing problem. Finally, the data representing the relative distances among the nodes of all three test runs is analyzed. The measured data with the sample mean is shown in Figure 3, and the sample variance of the measured data is shown in Figure 4.

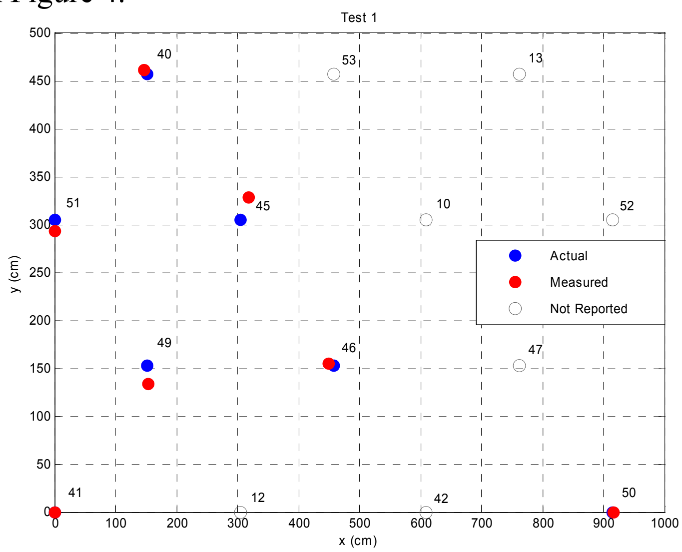


Figure 1: Estimated positions of the nodes using the VU algorithm of the first test run.

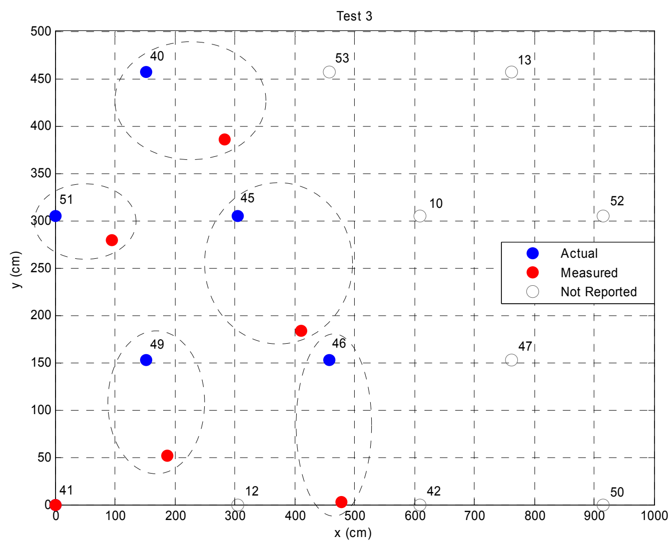


Figure 2: Estimated positions of the nodes using the VU algorithm of the third test run.

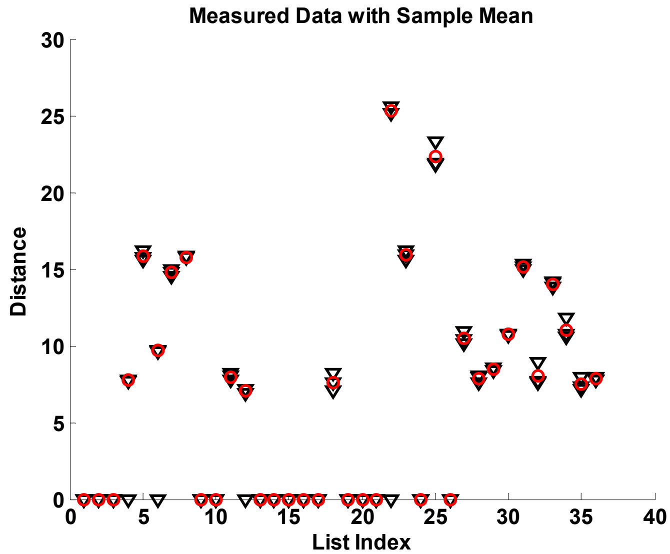


Figure 3: Measured data and sample mean of all three test runs

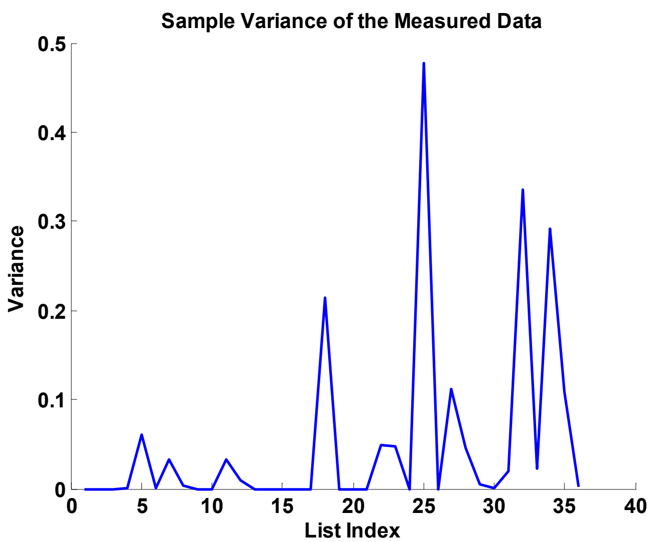


Figure 4: Sample variance of the measured data of all three test runs.

`We performed similar tests on the data with the ISOMAP algorithm, though with less than spectacular results so far. However, our investigation is in the beginning stages and we have not had time to investigate ways to optimize the performance. An example plot is shown in Figure 5.

A simple test of the quality of the approximation is provided by computing the residual variance, which gives a measure of the degree of variance in the original data, in this case the exact distance measurements, which are known, that has not been captured by the approximation. The residual variances are shown below in the Table 1. As can be seen, results from the ISOMAP algorithm are less than spectacular, but this is not surprising since we have only just begun to investigate use of this algorithm for this purpose.

Data Set	VU algorithm	ISOMAP algorithm
1	1.26E-03	2.63E-03
2	1.99E-03	6.28E-02
3	6.19E-03	1.52E-01

Table 1: Residual variances for two different algorithms tested for three data sets.

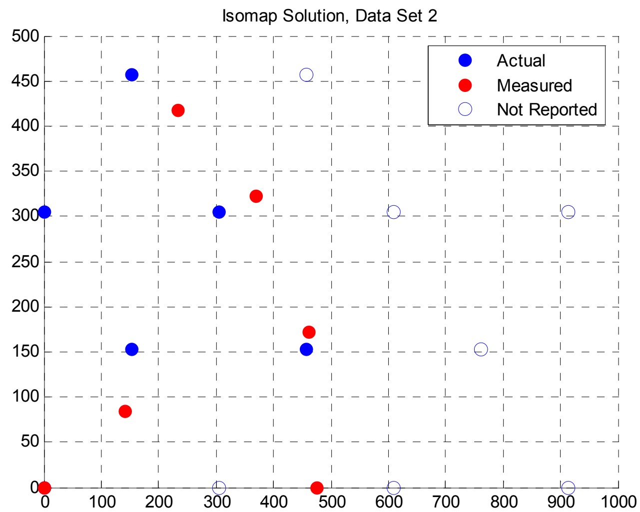


Figure 5: Estimated positions of nodes using ISOMAP algorithm of second test run

Another self-localization algorithm that we have started to investigate is by Neal Patwari *et al* [PAK2005]. Patwari estimates the position of the nodes via the Cramér–Rao Bound (CRB). He first measures the relative distances of any pair of nodes using the TOA or the Received Signal Strength (RSS), and then estimate their positions using CRB. However, the positions of a certain number of nodes must be known *a priori* to get a good estimate of the positions of all the nodes. This method is of interest to us because it scales well with very large networks, and it will be further investigated.

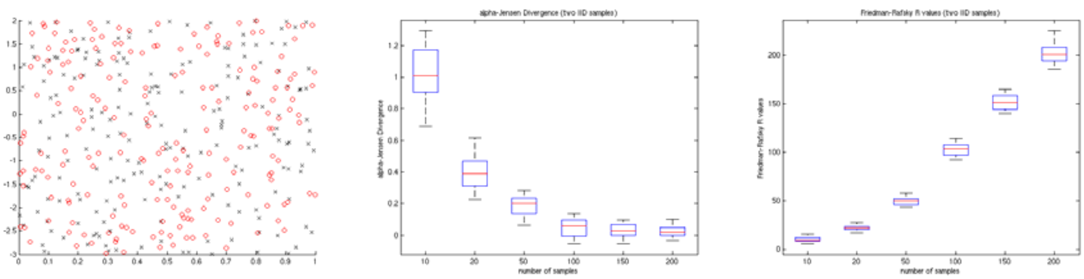
Although at the beginning it was mentioned that a good self-localization algorithm was critical for the shooter localization of the DARPA IXO NEST program, it is also critical for tracking algorithms such as the one being developed by Arizona State University under this ISP program. Therefore, our intention is to develop a reliable and accurate self-localization algorithm that serves as the cornerstone of other applications that rely on the known location of the sensors.

2.A.1.b. High Dimensional Data Processing Evaluations

The accurate estimation of divergence between class-conditioned high-dimensional data sets is a major theme of ISP. We have used Hero's entropic spanning graphs to estimate the α-entropy and quantified divergence using α-Jensen measure of divergence. This technique has been invaluable for quantitative analysis of 'information' content in datasets of interest, but we have determined that in cases of small samples, the α-Jensen divergence measure can be highly biased.

To deal with low-sample situations, we have augmented our tools for estimation of divergence via incorporation and use of the two sample multivariate Friedman-Rafsky test and associated statistic, which provides a distribution-free measure of separation between two distributions. It is a multivariate generalization of the Wald-Wolfowitz runs test. The technique is graph-based, with a minimal spanning tree constructed from the union of the two samples with class (sample) labels. The test statistic *R* corresponds to the number of disjoint subgraphs generated by removing all edges of the tree that connect vertices (data points) with differing labels.

We have found that this statistic can provide some robustness to samples of small size, as demonstrated in Figures 6 and 7 below. Figure 6 compares the statistical estimates from 20 random tests, each test drawing two samples from the same underlying distribution with a selected number of samples. In all cases, the expected α-Jensen divergence should be 0, and the expected value of the *R* statistic is N_i, the cardinality of each sample.



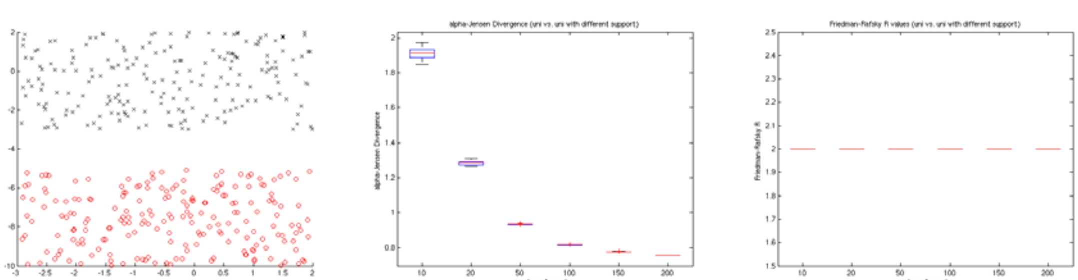
(a) **(b)** **(c)**

Figure 6: Low-sample statistic sensitivity to sample cardinality N_i for two samples drawn from the same underlying distribution. Figure (a) shows the two samples. Figures (b) and (c) respectively characterize the α-Jensen divergence and Friedman-Rafsky R-statistic estimates for $N_i = \{10, 20, 50, 100, 150, 200\}$ samples (total $N = N_1 + N_2$).

Note that the α-Jensen divergence does converge to the correct value, but is biased for small samples. The R statistic, however, tracks its expected value, even for small N_i.

Figure 7 demonstrates the effect of sample size when the distributions are disjoint. Again, the α-Jensen divergence measure converges, but is biased for small samples, while the Friedman-Rafsky *R* statistic is robust to sample size.

Friedman and Rafsky discussed improving the power associated with their test, by generalization of the statistic to the case of a graph consisting of a union of orthogonal-spanning trees. We have incorporated this alternative form and are evaluating its use for quantifying the separation between class-conditioned datasets of ISP interest.



(a) **(b)** **(c)**

Figure 7. Low-sample statistic sensitivity as a function of sample size given two disjoint distributions. Figure (a) examples samples from the disjoint distributions. For N_i = {10, 20, 50, 100, 150, 200} samples of each class (total samples $N = N_1 + N_2$), figure (b) displays the α-Jensen divergence scores while figure (c) illustrates the Friedman-Rafsky R-statistic values.

2.A.1.c. Polarization-Resolution Trade Study for SAR Imagery

Our initial evaluation is a polarization/resolution trade study using the two-target data collected in April, 1989, with the Advanced Detection Technology Sensor (ADTS) operated by MIT Lincoln Laboratory. The ADTS is a fully polarimetric, air-to-ground SAR sensor operating at Ka-band. The pixel spacing is nine inches, and the SAR image resolution is twelve inches. Three polarizations are concurrently measured – HH, HV, and VV.

In our investigation, we measure information divergence between the two targets as the available number of polarizations and the image resolution are varied. The two targets are an M48 tank ("T2") and an M55 self-propelled howitzer ("T4"). The targets are measured both in the open (Mission 77) and under radar scattering nets (Mission 83). In Mission 77, there are 228 images of T2 and 227 images of T4. In Mission 83, there are 68 images of T2 and 67 images of T4. These images were collected at a fixed depression angle of 22.5º. The target aspect angle was varied over 360º. While relative aspect angles are given for each target in each mission, the absolute target angle is unknown. The data from Mission 77 and Mission 83 is considered in the public domain, not subject to ITAR constraints. The data is available at https://www.sdms.afrl.af.mil/datasets/adts/.

Target-centered chips (128 pixels x 128 pixels) have been manually extracted, with magnitude and phase available at each pixel location. We take the central 60 pixel x 60 pixel region, and use only the pixel magnitude. Since the data has already been relatively RCS-calibrated as well as polarization-calibrated, no additional scaling or normalization is performed. For reducing image resolution, non-overlapping blocks of pixels in the reduced-resolution image are formed by taking the average value of the pixels in the corresponding pixel block of the original image. We use block sizes of 1x1 (original image), 2x2, 3x3, 4x4, 5x5 and 6x6. Since the original resolution is 12" and the pixel spacing is 9", the blocking process produces images with an effective resolution of approximately 12", 21", 30", 39", 48" and 57", respectively. The images are then vectorized, forming column vectors with 60x60 = 3600 elements. For a given resolution, concurrent SAR images at each of three polarization states are available. Information from different polarization states is combined by concatenating the respective data vectors (rather than averaging the data vectors). In addition, images from all three polarization states have been combined using the Polarization Whitening Filter (PWF). The PWF is designed to optimally reduce speckle.

Information divergence is used as the measure of target separability. The information divergence between the two targets is given by:

$$\text{Information Divergence} = -\ln(S). \quad (1)$$

In Equation 1, S is the Friedman-Rafsky test statistic calculated using three orthogonal MSTs. Larger values of information divergence indicate greater target separability. The results are given in Table 2 and Table 3.

Mission 77	HH	HV	VV	HHHV	HHVV	HVVV	HHHVVV	PWF
12”	354	354	370	355	377	373	380	399
21”	513	479	501	506	527	513	522	506
30”	568	523	572	579	585	577	590	577
39”	601	557	586	611	618	597	628	590
48”	605	570	605	605	611	592	609	593
57”	616	572	614	624	620	620	622	607

Table 2. Information divergence between data vectors from an M48 tank and an M55 howitzer, targets placed in the open.

Mission 83	HH	HV	VV	HHHV	HHVV	HVVV	HHHVVV	PWF
12”	151	188	170	160	169	171	175	168
21”	195	198	208	199	203	208	205	202
30”	206	203	199	208	204	204	204	204
39”	206	212	209	210	208	211	213	210
48”	210	210	209	212	213	209	213	208
57”	213	207	209	213	209	209	213	205

Table 3. Information divergence between data vectors from an M48 tank and an M55 howitzer, targets placed under radar scattering nets.

ISOMAP, a recently developed method for nonlinear dimensionality reduction/manifold extraction, is applied to the various resolution/polarization combinations for Mission 77 data and Mission 83 data in separate runs. The ISOMAP algorithm is used in the k-nearest-neighbor mode, with k=6. The first ten ISOMAP embedding coordinates are retained. Equation 1 is again used to measure information divergence, this time on the ISOMAP embedding coordinates. Results are given in Table 4 and Table 5.

Mission 77	HH	HV	VV	HHHV	HHVV	HVVV	HHHVVV	PWF
12”	286	246	283	303	304	315	343	379
21”	478	422	458	479	463	461	488	505
30”	556	488	540	554	569	554	558	550
39”	596	512	578	610	585	583	611	579
48”	598	527	585	593	598	589	610	580
57”	598	556	606	608	611	598	636	585

Table 4. Information divergence between ISOMAP embedding coordinates for an M48 tank and an M55 howitzer, targets placed in the open.

Some comments are in order. First, from Table 1 and Table 2, it is apparent that for a fixed polarization case, the information divergence increases as the resolution is coarsened, appearing to converge more rapidly at the lowest resolutions for the targets under radar scattering nets (Figure 1). There is less information divergence for the targets under netting than for the targets in the open (Figure 8).

Mission	HH	HV	VV	HHHV	HHVV	HVVV	HHHVVV	PWF

83								
12”	163	192	160	161	158	151	151	149
21”	191	210	194	199	187	199	189	197
30”	203	211	201	203	205	203	203	201
39”	197	211	209	211	205	211	205	211
48”	205	211	205	205	207	207	211	211
57”	211	205	205	211	207	205	211	207

Table 5. Information divergence between ISOMAP embedding coordinates for an M48 tank and an M55 howitzer, targets placed under radar scattering nets.

Generally, it is considered that degrading resolution should decrease information divergence. However, for this data set – the ADTS sensor observing the M48 tank and M55 howitzer – it may be the case that by coarsening resolution, deleterious effects due to speckle are minimized (noise is diminished), whereas dissimilarity between the two targets is more evident at spatial scales greater that the original data resolution of 12 inches (signal is not diminished as much). This results in an overall improvement in the signal-to-noise ratio.

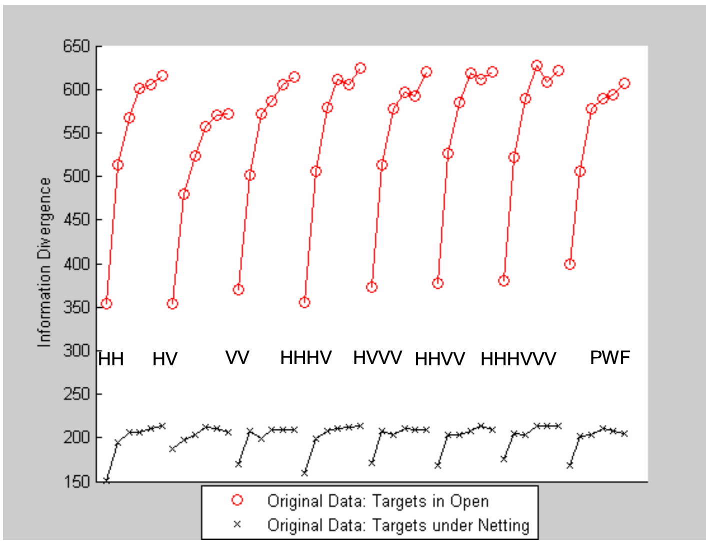


Figure 8. Information divergence for different polarization combinations, targets in open and targets under netting. Within each polarization combination, resolution coarsens moving from left to right.

From Tables 2 and 5, and Tables 3 and 5, it is apparent that the first ten ISOMAP embedding coordinates preserve the majority of the information divergence seen in the original high (3600-) dimensional imagery (Figures 9-10). The ability of ISOMAP to capture the information divergence inherent in the original high-dimensional data with just ten embedding coordinates improves as the resolution is coarsened (Figures 9-10).

For targets in the open, the information divergence increases slowly as more polarizations are used. For targets under the radar scattering nets, there is no discernible benefit in using multiple polarizations. We will continue this line of inquiry using the ADTS data set. We will also investigate information divergence variation with degradation of image resolution for other data sets.

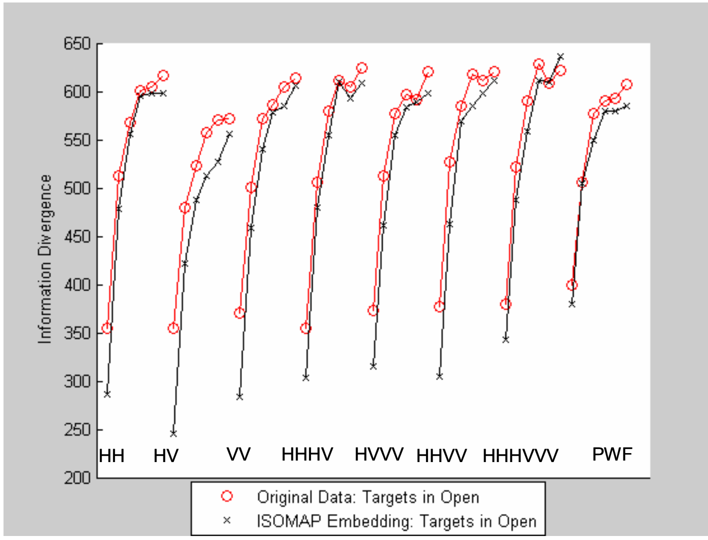


Figure 9. Information divergence for different polarization combinations, targets in open. Within each polarization combination, resolution coarsens moving from left to right.

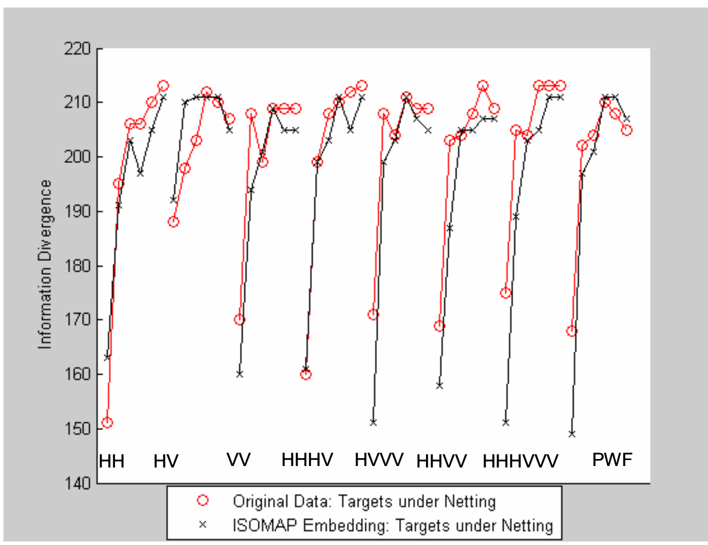


Figure 10. Information divergence for different polarization combinations, targets under netting. Within each polarization combination, resolution coarsens moving left to right.

2.A.1.d. CADSP UCIR Evaluation Technical Support

There is currently a great deal of interest in UCIR sensors within the Department of Defense community in Automatic Target Acquisition (ATA) for smart munitions. A prime example of such a weapon system is the NetFires NLOS PAM that is being developed jointly by Raytheon and Lockheed Martin under U.S. Army sponsorship. The obvious attraction of UCIR sensors over the more traditional cooled sensors is their low cost. The trade-off for achieving this greatly reduced cost is degradation in image quality that places a significantly greater burden on the ATA algorithms.

We believe that the Georgia Tech CADSP imager has potential for improving the performance of the PAM UCIR imager. We are investigating its application for *on-Focal Plane Array* (FPA) pre-processing operations. The NetFires NLOS PAM currently uses a chopper wheel to implement Non-Uniformity Compensation (NUC) for it UCIR sensor.

We are evaluating whether the CADSP can be used instead; this should result in reduced cost/complexity and improved performance. One of the most difficult aspects of performing ATA using UCIR sensors is the extremely low contrast quality of the image. Traditional equalization approaches (*e.g.,* histogram equalization) tend to perform very poorly and it is likely that a localized, non-linear equalization approach is needed. We are investigating whether the CADSP would enable implementation of such algorithms on the UCIR sensors. Given ISP Phase II funding constraints, we will limit these pre-processing investigations to an evaluation of their implementation on the Georgia Tech CADSP imager.

2.A.2. ASU Technical Progress

2.A.2.a. Tracking and Sensor Scheduling with Motes Demonstration

Wireless sensor nodes (such as Berkeley motes) are now commercially available and can be used to form large scale sensor networks to perform a variety of sensing tasks. However, the long-term effectiveness of a sensor network is critically dependent on network energy consumption. We have developed sensor scheduling algorithms to minimize the energy consumption of a sensor network while maintaining a desired tracking accuracy for a target moving through the network. We formulate this problem as a discrete constrained optimization problem where the objective function is total network energy costs and the constraint is a maximum allowable predicted tracking error. In our formulation, we have investigated predicting the tracking error using both the posterior Cramer-Rao bound and Monte-Carlo (MC) based-techniques.

We investigated the performance of the developed scheduling algorithm using MC simulation; the network node energy models were based on the specifications of the Berkeley Mica2 mote sensor. These simulations showed that the prediction of the tracking accuracy by the posterior Cramer-Rao lower bound based scheduler is very optimistic when compared to the ground truth for acoustic energy sensors. As a result, the scheduler allocates less sensing resources than necessary for tracking and fails to meet the tracking accuracy. On the other hand, the tracking accuracy predicted using the MC based scheduling technique is much closer to the ground truth. As a result, MC based sensor scheduling results in significant network energy savings while meeting the desired sensing task.

In addition to developing sensor scheduling algorithms, we are also implementing a testbed network using Berkeley motes; currently we are interfacing the motes, collecting data, and performing some basic processing using LabView and Matlab. We are also characterizing and modeling the acoustics sensor on the motes.

In addition to sensor scheduling in sensor networks, we also investigated waveform configuration for agile sensing. Specifically, we considered the problem of characterizing the tracking performance of linear and nonlinear frequency modulated chirps with a trapezoidal envelope. The waveforms were compared using the conditional variance of the errors in estimating the range of a target given its range-rate. It was found that the exponential chirp offers the best performance. These findings were applied to a simulation study in which two waveform-agile sensors track a target's Cartesian position coordinates and velocity components and employ dynamic selection of linear, parabolic, hyperbolic, exponential and power chirps so as to obtain the lowest predicted mean square error. The results of the simulations match those of the characterization study.

2.A.2.b. Multiple Target Tracking using the Configurable CADSP Imager

The Georgia Tech team is developing a novel CADSP imager that will provide unique configuration and computational opportunities to an integrated sensing processing system. In particular, the imager can be configured to either compute optical flow or image selective sub-areas of the field of view. This sensor will be used in the Phase II demonstration, in which the sensor is dynamically configured to accurately track targets. We are currently developing the configuration and tracking algorithms for this demonstration. In particular, we are working on a measurement model for the sensor and its novel computation of optical flow. This model will be integrated into our multiple target tracker and configuration algorithms to implement the demonstration.

An important capability for the target tracker is the incorporation of information other than the observed measurements into the target state estimate. Such information may result from motion constraints on the moving objects and their interactions with each other and the environment. Thus, we have incorporated deterministic and stochastic target kinematic constraint information into a particle filter to improve the tracking performance of multiple targets. Using simulations, we demonstrated the improved performance of the proposed algorithm over the independent partitions multiple target tracking algorithm.

2.A.3. Georgia Tech Technical Progress

2.A.3.a. CADSP Algorithms Status

Two types of optical flow processing have been investigated:

The first type uses more traditional methods with an emphasis on mitigating the impact of noise on optical flow estimation. The goal is to develop algorithms that effectively estimate optical flow in the presence of imager noise. CMOS imager platforms usually have a digital processing step to reduce noise, especially fixed-pattern noise. Since the goal is to perform processing on the sensor, the optical flow algorithms need to be robust against both fixed-pattern noise inherent to CMOS imagers and signal-related noise commonly that observed with uncooled IR images. The primary result of this research will be some calibration methods that may be used to estimate the noise effect and combat it downstream from the on-imager processing. These methods will work with the existing CADSP imager system.

The second type of processing involves some slight changes to the CADSP imager system and is designed to take advantage of the fact that the processing done on the imager uses continuous, not sampled, signals. In this system the CADSP imager is set to perform edge detection. The resulting signal is fed into a bank of small band-pass filters that operate temporally on a pixel basis. The output of these filters represents motion as a positive or negative "blip" which can then be detected and converted to a digital signal at a relatively low frame rate (such as 30 FPS). The advantage of such a system is that motion may be directly estimated in real-time without the need for large search windows. Currently, motion estimation system is being simulated at the algorithmic level and measurements from the imager IC are being taken to ascertain the feasibility of such a system.

2.A.3.b. CADSP Hardware Status

The hardware investigation continues into the development of a CMOS imager which can perform initial calculations on sensory input to facilitate low power computational sensory systems. To sustain investigation of the CADSP imager technology in the initial absence of funding, a one megapixel imager was fabricated in December 2004. At this time testing of that imager is in progress. The one mega pixel imager was designed to test the CADSP imager technology at a full scale implementation. In addition, various custom testing PCB's have been designed and manufactured along with the development of a testing system including FPGA and processor integration. Testing is about at a half way point and IC subsystems thus far are at least operational. The chip has about six main sections. An initial system which uses analog floating gates to store and provide analog values to the imager pixel array has been programmed and read. The pixel plane with multiplication at the pixel level has initially shown operation. A readout system with wide dynamic range capability has also been tested and has shown operation. The back end of the chip contains offset correction, an analog vector-matrix multiplier and an analog to digital conversion. These systems remain to be tested along with the refinement of the operation of the front end subsystems.

2.A.4. UniMelb Technical Progress

2.A.4.a. Intrusion Detection/Tracking Using Motes and TDOA Geolocation

We consider the problem of detecting and tracking objects moving through a field of unattended wireless sensors. We model a "target" moving through the field as something creating sufficient impact by its movement to excite an accelerometer on a mote as a function of distance. Currently, following work done by Raytheon and ASU in ISP Phase I, we model the detection probability as a decreasing exponential function with distance: $P_D = c_0 \exp(-||x - x_T||^{2\sigma})$, where P_D is the probability of detection, c_0 is a constant denoting the probability of detection at zero range, x and x_T are the locations of the mote and target, and σ is a scaling parameter.

Motes are modeled as quite simple devices. Each mote remains “asleep” until its accelerometer is excited, at which point it merely transmits a unique identifying code. We assume that no further information is passed from the mote.

If the mote identification message can be heard by three receivers, then Time Difference of Arrival (TDOA) techniques may be used to locate the excited mote. Furthermore, as each mote’s code is known, the receivers may collect data at the appropriate frequencies, and cross correlate the collected data with the known codes. Thus, generating a time of arrival on each platform is relatively straightforward; Raytheon then hopes to leverage existing TDOA geolocation algorithms and software to locate the mote(s) that have detected a target.

Following detection, we are investigating algorithms to cluster motes to detect/track multiple targets. We are investigating using Gaussian Mixture Models to yield track estimates; one difficulty is that the number of clusters is an input, and rigorous methods to identify the “best” number of clusters are needed. Other clustering algorithms are also under consideration (*e.g.,* fuzzy c-means).

A variant of the clustering approach is also being studied. With this method, each collection or cluster of excited motes generates mutually exclusive "virtual" position measurements that depend on hypotheses concerning different numbers of targets. These measurements are treated as noisy target measurements; that is, they are regarded as having some probability of having been generated by clutter. These "virtual" measurements are then used as input to a conventional target tracking algorithm.

The "virtual" measurements for each cluster of motes are generated according to the assumptions listed below. These assumptions are not fundamental to this approach and how the method can be extended to cope with the relaxing of each of them is discussed later. The assumptions are:

- Motes always detect any target within range of the sensor;
- There are no false detections; and
- Mote locations are known exactly.

A "cluster" is defined as the smallest set of motes whose detection regions overlap those of an excited mote. A snapshot of the tracker output is shown below.

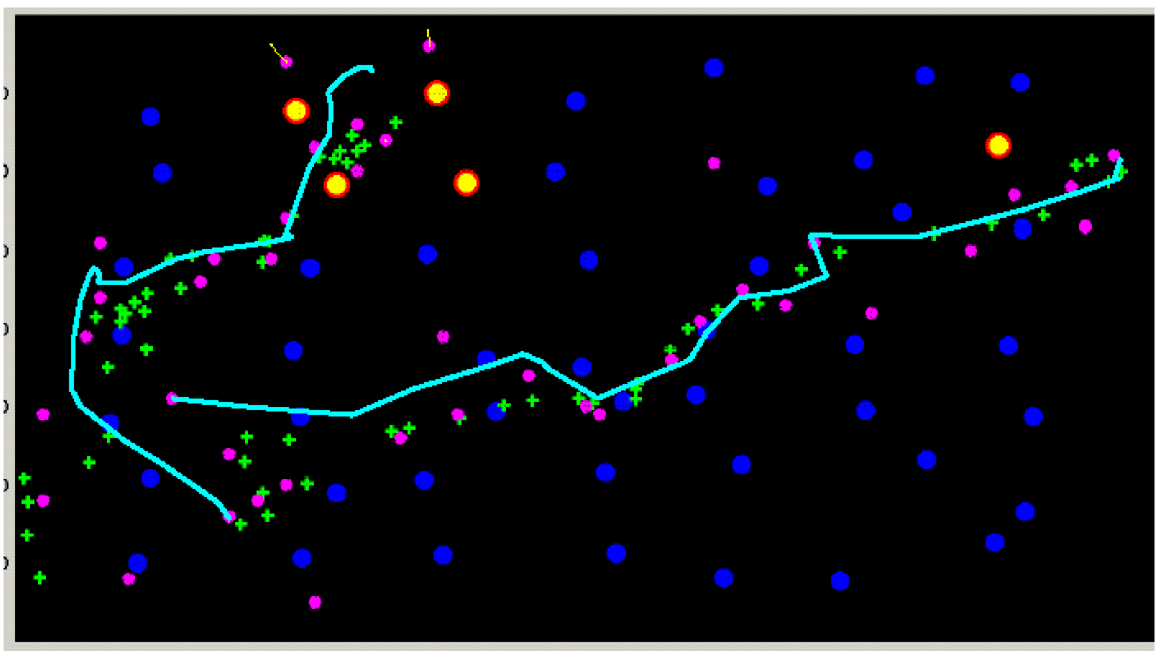


Figure 11. Tracker output snapshot. The inactive motes are shown in blue while motes currently excited are shown in yellow. Actual target paths up to the current time are shown by green crosses and all "virtual" measurements are shown in pink. Confirmed target tracks are given by the solid blue line.

As mentioned above, removal of the three assumptions currently in use is straightforward and does not require alterations to the framework of the tracker. Improvements in performance can also be gained by using a multiple target tracker in place of the single target IPDA currently used. This is being investigated. A better approach might be to use an MHT-style tracker. This too will be investigated over the next reporting phase. We also believe that much of this algorithm can be localized.

2.A.4.b. Coordinated UAV Evaluation

We consider the case of dynamic repositioning and scheduling of passive RF receivers for TDOA geolocation. Preliminary work has loosely been divided into stages:

1. Determination of appropriate cost functions, including algebraic manipulation and simplification.
2. Given a target area and initial positions of receivers, control the flight paths of the receivers to minimize cost.
3. Given a target area and initial positions of many static receivers, dynamically schedule the receivers to take measurements to "best" geolocation the target.

The work is preliminary in that the receivers are assumed to detect the target without fail (*i.e.,* $P_D = 1$). Future work should encompass the fact that P_D is a function of relative angle to the radar antenna, generating a trade-off between positioning for better geolocation accuracy and maximizing detection probability. Unfortunately, we would require the direction of the main beam of the radar, and a model of the antenna pattern. This complicates matters because the direction of the beam is dynamic, and suitable models of antenna patterns are not smooth, due to nulls. Finally, the existing work is using a myopic, full-information approach. A paper is being prepared for publication [2].

Another aspect of the work being done at UniMelb builds on an earlier effort (prior to this contract) on a one-step ahead algorithm for trajectory control of a single platform with ESM using bearings only tracking to locate multiple stationary or slowly moving emitters. Our new effort focuses on tracking of a single moving target by multiple UAV with either bearings only or TDOA sensors. No clutter is assumed and noise on both the trajectory of the target and the sensor measurements was assumed independent and Gaussian. An extended Kalman filter was used for tracking. This should not be seen as a limitation of the algorithm, however, as the method assumes that any suitable tracking algorithm can be "plugged in."

The idea of the method is the following:

1. At each time the posterior estimate of the target location is computed, the next waypoints of the UAVs are calculated by minimizing a cost function, using the constrained optimization algorithm.
2. Then a new set of measurements is acquired from the newly located UAVs.
3. The cost function is chosen to be mutual information between the measurements and the state estimate of the target.
4. Constraints in these examples are imposed on the velocities of the UAVs and their distances from the target. The constraints can be extended to account for a terrain situation, threats from other objects, angle of maneuver of the UAVs, *etc*.

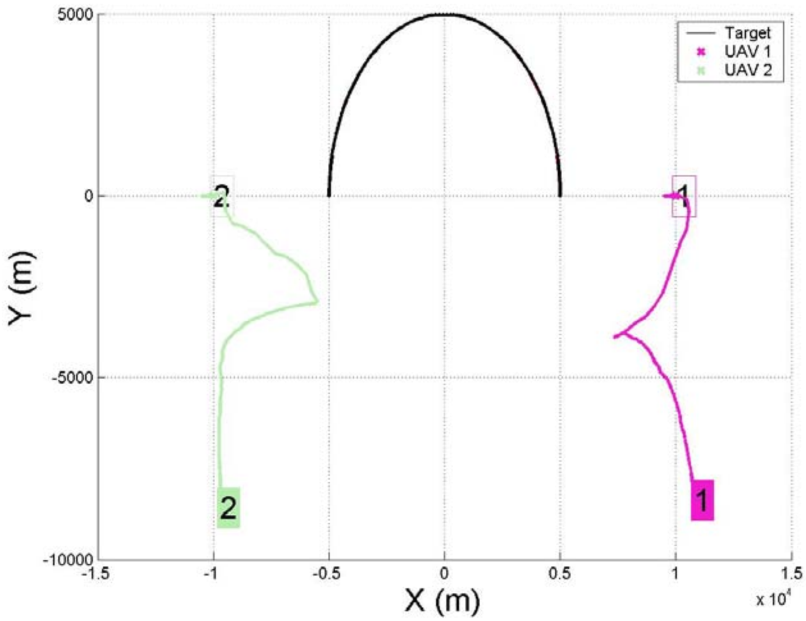


Figure 12: Optimal trajectories of 2 UAVs tracking a slow moving target on a half-circular trajectory, using bearings only sensors.

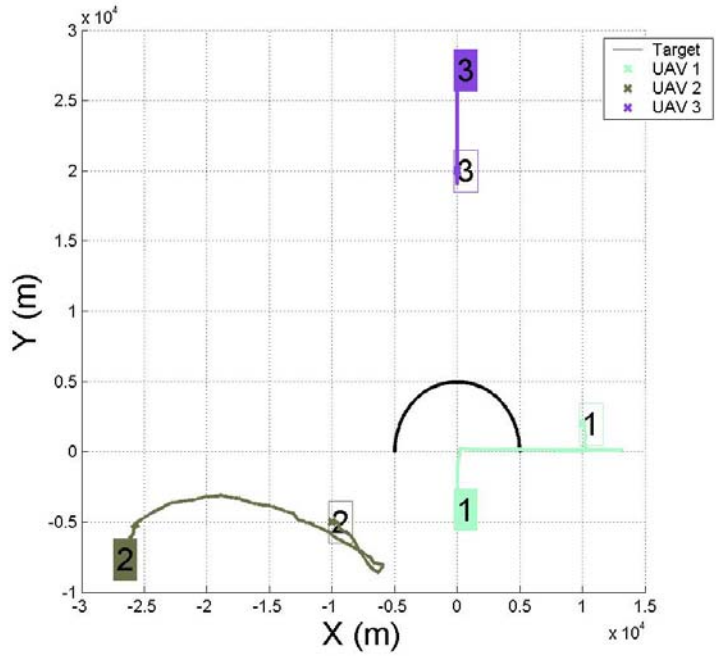


Figure 13: Optimal trajectories of three UAVs tracking a slow moving target on a half-circular trajectory using TDOA sensors.

2.A.4.c. Myopic versus Multiple Epoch

We aim to extend the work of Howard, Suvorova, and Moran, [HSM2004], who consider the optimal scheduling of two Gauss-Markov systems with the aim of minimizing the sum of the variances. As a side problem, we can show that, given M systems that evolve in a Gauss-Markov framework, if the cost is the sum of the variances at some time, T, and each system can be measured only once, then it is optimal to measure the T-highest systems in increasing order (rather than decreasing, which would be the greedy approach). In this limited case, the optimal measuring scheme is the reverse of the greedy scheme.

This result, while counterintuitive, is rather straightforward to derive. As noted in [HSM2004], measuring reduces the variance of a measured system, from σ^2 to $(\sigma^2+Q^2)R^2/(\sigma^2+Q^2+R^2)$, where Q^2 and R^2 are the process variance and measurement variance, respectively. If a system is not measured, then σ^2 grows to σ^2+Q^2. Thus, making a measurement *after* n steps causes the variance to become:

$$\sigma^2_{n+1} = (\sigma^2 + nQ^2)\, R^2 /(\sigma^2+nQ^2+R^2),$$

whereas the growth of σ^2 while measuring at the first possible time yields:

$$\sigma^2_{n+1} = (\sigma^2+Q^2)\, R^2 / (\sigma^2+Q^2+R^2)+(n-1)Q^2$$

where the first term on the right represents measuring the system at time 0, with the corresponding growth of the system over the horizon after the system is measured, using the constraint that each system may be measured only once. Taking the difference between the two equations for σ^2_{n+1} shows that measuring later is better; this shows that measuring the systems in increasing order of variance may be done by using interchange arguments.

2.A.5. UM Technical Progress

Our principal goal during this phase of the project has been to exploit classification theory for classifier-driven dimension reduction and waveform design problems.

2.A.5.a. Dimension/Classifier reduction for optimal scheduling problems.

Previous dimension reduction approaches have sought to maximize goodness of fit to the data, *i.e.* match data geometry, without regard to impact on classification performance. Examples include: principal components, ISOMAP, and Laplacian Eigenmap (LE); they all find projections that minimize a quadratic penalty by solving an eigen-decomposition problem. Our approach accounts for both goodness of fit and classification. The unifying theme here is the use of variational methods to produce dimension reductions that minimize a classification-penalized embedding error. Two methods are being explored. The first is a quadratic formulation that extends the LE method of Beylkin *et al.* and is called Classification Constrained Dimension Reduction (CCDR). Progress on implementing the CCDR formulation is described in detail in our publication [Costa&Hero:ICASSP05].

Optimal scheduling of sensors and waveforms was an integral part of the ISP Phase I program. When the observation model under all possible scheduling actions is known, optimal scheduling is straightforward in the POMDP framework. On the other hand, in many applications the model is unknown and the risk function has to be estimated from the data. Under an assumption that trajectories of the measurements and the sequence of rewards can be generated by simulation or experiment, a reinforcement learning (RL) framework can be developed that is based on mapping the action policy optimization problem to an optimal label classification problem. We have established a general theory of exact classifier reduction of such RL problems that allows powerful optimal classifiers such as support vector machines, tree classifiers, and neural network classifiers to be applied to sensor scheduling and other optimal resource allocation problems [Blatt&Hero:NIPS05]. We are currently applying this to selection of optimal waveform dictionaries for waveform scheduling in radar tracking systems [Waagen&etal:05]].

2.A.5.b. CADSP Demonstration and Evaluation Technical Support

We have held several discussions with Paul Hasler and David Anderson on adapting our algorithms to the CADSP architecture. Given how ubiquitous matrix eigen-decompositions are in waveform design, dimension reduction, and statistical inference, it is clear that one of the most promising applications would be to implement SVD's in hardware. A diffusion based algorithm for accomplishing this task was jointly developed at one of our meetings. However, it appears that the hardware is not yet ready for such an ambitious task. We have discussed alternatives such as fast local matched filtering and segmentation of images and optical flows. These functions would be very useful for rapid collection and preprocessing of features from images to which our dimension reduction techniques could be applied.

2.A.6. FMAH Technical Progress

No input received.

2. B. Publications

There were no refereed publications that occurred during the current PoP.

1. Chetri, D. Morrell and A. Papandreou-Suppappola, "Non-myopic sensor scheduling and its efficient implementation for target tracking applications," under revision for EURASIP Journal on Applied Signal Processing, July 2005.

2. C. Conference Proceedings

There were no publications in conference proceedings during the current PoP.

1. "Radar Waveform Selection Using Weighted Classification for T-Step Policy Search," D. Waagen, C. Savage, H. Schmitt, N. Shah, A. Hero, W. Moran, and S. Suvorova, 2006 IEEE International Waveform Diversity and Design Conference, abstract submitted.
2. "Positioning and Scheduling UAVs for Passive Geolocation," Craig O. Savage, Harry A. Schmitt, Robert Cramer, and William Moran, Infotech@Aerospace, 26-29 September 2005, Arlington, VA, in preparation.
3. D. Blatt and A. O. Hero, "From weighted classification to policy search", submitted to NIPS June 2005.
4. A. Chhetri, D. Morrell and A. Papandreou-Suppappola, "Energy efficient target tracking in a sensor network using non-myopic sensor scheduling," IEEE Information Fusion, Philadelphia, PA, July 2005.
5. S. Sira, A. Papandreou-Suppappola and D. Morrell, "Characterization of waveform performance in dynamically configured sensor systems," invited to the International Waveform Diversity and Design Conference, Kauai, Hawaii, January 2006.

6. I. Kyriakides, D. Morrell and A. Papandreou-Suppappola, "Multiple target tracking with constrained motion using particle filtering methods," accepted to the Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, California, October 30 - November 2, 2005.
7. I. Kyriakides, D. Morrell and A. Papandreou-Suppappola, "Sequential Monte Carlo methods for tracking multiple targets with stochastic kinematic constraints," invited to the First IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing, Puerto Vallarta, Mexico, December 2005.

2. D. Consultative and Advisor Functions

There were two consultative or advisory functions that occurred during the current PoP. The first relates to a Raytheon Shooter Localization demonstration using the Crossbow wireless sensor nodes. This work is being funded under the DARPA IXO NEST Phase II program. The Phase I shooter localization algorithms were developed by VU. Preliminary results indicated that the shooter localization algorithm has significant potential. The program was subsequently classified and was ultimately transitioned to Raytheon for demonstration and refinement under Phase II. The DARPA IXO Program Manager has kindly given permission for several of these algorithms to be used in our ISP Phase II program. The Raytheon NEST program has identified a critical need for the development of an accurate sensor localization algorithm that is scalable to hundreds or thousands of nodes. Indeed, the DARPA NEST program hopes to demonstrate a 10,000 node network. We have identified several promising mathematical approaches to sensor localization (*c.f.,* Section 2.A) that will be made available to the Raytheon NEST program.

The second function relates to the NetFires NLOS PAM. NetFires NLOS PAM employs a UCIR sensor for target recognition. We believe that NetFires NLOS is a compelling target transition program for the Georgia Tech CADSP imager being investigated on our ISP Phase II program. A preliminary contact has been made with the NLOS sensor lead and we are working to set up a technical meeting.

2. E. New Discoveries, Inventions or Patent Disclosures

There were no patent disclosures filed during the current PoP.

2. F. Honors/Awards

There were no honors or awards received during the current PoP.

2. G. Transitions.

There were no technology transitions achieved during the current PoP.

2. H. References

[Blatt&Hero:NIPS05] D. Blatt and A. O. Hero, "From weighted classification to policy search," submitted to NIPS June 2005

[Costa&Hero:ICASSP05] "Classification constrained dimensionality reduction," J. Costa and A. O. Hero, *Proc. of ICASSP*, Philadelphia, March, 2005.

[Hero&Michel:SSP99] "Estimation of R'enyi Information Divergence via Pruned Minimal Spanning Trees," A. O. Hero and O. Michel, *1999 IEEE Workshop on Higher Order Statistics*, Caesaria ISRAEL, 1999.

[HSM2004] "Optimal Policy for Scheduling of Gauss-Markov Systems," S. Howard, S. Suvorova and B. Moran, 7th *International Conference on Information*, Stockholm, Sweden, 2004

[Maroti2005] "Radio Interferometric Positioning," M. Maroti, *et al, Technical Report TR #: ISIS-05-602*, Institute for Software Integrated Systems Vanderbilt University, Nashville, Tennessee, 2005.

[PAK2005] "Locating the Nodes: Cooperative Localization in Wireless Sensor Networks," N. Patwari, J. Ash, S. Kyperountas, A. O. Hero, R. M. Moses and N. S. Correal, IEEE Signal Processing Magazine, special issue on Signal Processing in Positioning and Navigation, 22, **4**, pp. 54-69, 2005.

2. I. Acronyms

ADTS	Advanced Detection Technology Sensor
ASU	Arizona State University
ATA	Automatic Target Acquisition
AVU	Algorithms Verification Units
CADSP	Cooperative Analog Digital Signal Processor
CRB	Cramér–Rao Bound
DARPA	Defense Advanced Research Projects Agency
FPA	Focal Plane Array
FMAH	Fast Mathematical Algorithms and Hardware
Georgia Tech	Georgia Institute of Technology
GPS	Global Positioning System
ISP	Integrated Sensing and Processing
IXO	Information Exploitation Office
MC	Monte-Carlo
NEST	Networked Embedded System Technology
NLOS	NetFires Non-Line of Sight
NUC	Non-Uniformity Compensation
ONR	Office of Naval Research
PAM	Precision Attack Munition
PWF	Polarization Whitening Filter
PoP	Period of Performance
RISCO	Raytheon International Support Company
RSS	Received Signal Strength
TAA	Technical Assistance Agreement
TDOA	Time Difference of Arrival
TIM	Technical Interchange Meeting
UAV	Unmanned Aerial Vehicle
UCIR	Uncooled infrared imaging
UM	University of Michigan
UniMelb	Melbourne University
VU	Vanderbilt University